Staff Paper

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Abstract

This paper introduces a spatial bioeconomic model for study of potential cellulosic biomass supply at regional scale. By modeling the profitability of alternative crop production practices, it captures the opportunity cost of replacing current crops by cellulosic biomass crops. The model draws upon biophysical crop input-output coefficients, price and cost data, and spatial transportation costs in the context of profit maximization theory. Yields are simulated using temperature, precipitation and soil quality data with various commercial crops and potential new cellulosic biomass crops. Three types of alternative crop management scenarios are simulated by varying crop rotation, fertilization and tillage. The cost of transporting biomass to a specific demand location is obtained using road distances and bulk shipping costs from geographic information systems. The spatial mathematical programming model predicts the supply of biomass and implied environmental consequences for a landscape managed by representative, profit maximizing farmers. The model was applied and validated for simulation of cellulosic biomass supply in a 9-county region of southern Michigan. Results for 74 cropping systems simulated across 39 sub-watersheds show that crop residues are the first types of biomass to be supplied. Corn stover and wheat straw supply start at $21/Mg and $27/Mg delivered prices. Perennial bioenergy crops become profitable to produce when the delivered biomass price reaches $46/Mg for switchgrass, $118/Mg for grass mixes and $154/Mg for Miscanthus giganteus. The predicted effect of the USDA Biomass Conversion Assistance Program is to sharply reduce the minimum biomass price at which miscanthus would become profitable to supply. Compared to conventional crop production practices in the area, the EPIC-simulated environmental outcomes with crop residue removal include increased greenhouse gas emissions and reduced water quality through increased nutrient loss. By contrast, perennial cellulosic biomass crops reduced greenhouse gas emissions and improved water quality compared to current commercial cropping systems.

Keywords: biomass production, bioenergy supply, biofuel policy, bioenergy, cellulosic ethanol, agro-ecosystem economics, ecosystem services economics, agro-environmental trade-off analysis, mathematical programming, EPIC.

JEL codes: Q16, Q15, Q57, Q18

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1. Introduction

Current US energy policy aims to foster national energy independence and environmental stewardship by stimulating liquid biofuel production as substitute for fossil fuels [1]. In the pursuit of these goals, the US Energy Independence and Security Act (EISA) of 2007 mandates that 36 billion gallons of biofuel be produced by 2022, of which 16 billion gallons are to be derived from ethanol made from cellulosic biomass. Reaching such an ambitious cellulosic biofuel production target requires that commercial land managers produce and supply large quantities of biomass from agricultural residues and new perennial energy crops. Cellulosic biomass sources under consideration for ethanol production include agricultural residues and dedicated cellulosic biomass crops, such as the perennial grasses and short rotation tree crops. Past research suggests that the current agricultural system can supply desirable quantities of crop residues and farmers can grow new perennial energy crops using a fraction of current croplands if appropriate market incentives are provided [2, 3].The well-known Department of Energy report on producing a billion ton annual supply of biomass also recognized that for such a large quantity of biomass to be produced, a significant portion of current cropland would have to be converted into new cellulosic crops production in addition to the conservation reserve program (CRP) lands [4].

Although it is technically feasible to produce the large quantities of biomass needed, research is warranted to understand conditions under which rational profit maximizing farmers would willingly choose to provide such biomass. Of equal interest are the environmental implications of such new production activities. While the final quantity of biomass supplied will critically depend on prevailing market prices and production technology; there is also a need to know how the new energy policy would affect greenhouse gas fluxes (carbon dioxide [CO_2] and nitrous oxide [N_2O] emissions) and water quality changes that result from surface and sub-surface phosphorus [P] and nitrate [NO_3] losses. Efforts have been made in the study of these environmental issues at national scale [5-7], principally in determining the impact of biomass supply on greenhouse gas emissions and climate change. However, some environmental impacts such as soil erosion and nutrient loss affecting surface and groundwater water are best captured at watershed scale [8]. Understanding such environmental issues will help design appropriate policy incentives to reduce greenhouse gas emissions and improve water quality in a context of nonpoint pollution.

This paper integrates biophysical simulation of multiple crop and environmental outcomes, transportation information and economic profit optimization behavior to model the likely supply of biomass and associated land use environmental consequences at watershed scale. The model captures the opportunity cost to farmers of changing practices from growing current commercial crops to producing biomass from annual crop residues and perennial cellulosic crops. To reach this objective, the the terrestrial ecosystem model (Environmental Policy Integrated Climate) (EPIC) is used to simulate crop yield and environmental variables from various cropping systems in a spatially explicit manner. A regional mathematical programming model is developed to simulate the profit maximizing cropping system choices of representative farmers under prevailing market conditions. Transportation costs are included to evaluate the impact of transporting biomass to a centrally located biorefinery facility (or electrical power plant). This paper describes the model and answers the following research questions, 1) Under what price conditions would biomass production become attractive to profit-oriented farmers? 2) What is the sequence of crop production systems and associated land uses as biomass supply increases? 3) What are the environmental consequences of the changing crop production systems as biomass production increases? and 4) How are these results altered by provisions of the Biomass Conversion Assistance Program (BCAP) in the 2008 farm bill?

The remainder of the paper is organized as follows. First, we present a conceptual framework where the structure of the model is described with all its components. Second, an empirical application of this bioeconomic model to southern Michigan is described, including development of the parameters driving the model, and the model validation and calibration procedures. Third, we report results for the predicted biomass supply in response to rising price along with associated changes in land use and environmental outcomes. The paper concludes with observations about feasibility of biomass production, likely environmental consequences, the need for environmental policy simulation and desirable extensions of this bioeconomic modeling framework.

2. Conceptual Modeling Approach

2.1 Existing modeling approaches

While farmers have many business objectives, expected profitability has proven to be a powerful predictor of farmer behavior at farm and regional scales [9-11]. Land quality and quantity plus available cropping system technologies shape productive potential. Prices and transportation costs tend to influence strongly both cropping system profitability and the associated spatial distribution of land use by crops. Two modeling approaches have arisen in the literature as a result. The first approach regroups pure geographic information systems (GIS) approaches [12] and non-optimizing cost-benefit approaches [10, 13] of biomass supply modeling. The GIS modeling approach particularly helps understand the importance of transportation costs in the production and supply of biomass. These models are informative in giving general estimate of biomass supply potential without focusing much on the underlying economic agent behavior. However, as other authors have made it clear, for revenues to exceed costs by itself will not be a sufficient condition for a rational profit maximizing farmer to switch to new cellulosic crop production or crop residue collection [14]. Farmers also need to cover the opportunity cost of the crops that are displaced by biomass crops activities.

The second modeling approach includes all models that rely on farm profit maximization to derive biomass supply [15-17]. This group includes both representative farm profit maximization models and market-level economic surplus maximization models. While these models have the advantage of incorporating farmers' economic behavior, the information they offer on potential regional scale environmental impacts of changed landscape-level crop production tends to be scanty or available only at a large spatial scale, such as the county [16, 17]. The modeling approach presented here seeks to unite the strengths of both previous modeling approaches in a regional, spatial model that captures the opportunity cost on profitability and the environmental trade-offs of changed cropping system responses to incentives to supply cellulosic biomass. Since production system choices yield both marketed products and environmental outcomes, the analysis highlights instances where policy incentives may be needed to manage trade-offs between biomass productions and undesirable environmental externalities (such as increased water pollution or greenhouse gas emissions).

2.2 Structure of the Bioeconomic Model

The bioeconomic model is an integrated biophysical - GIS - economic regional mathematical optimization model. The biophysical component is a spatial crop simulation model that supplies crop yields and environmental outcomes to the bioeconomic model. The GIS component supplies transport distance and time parameters to the bioeconomic model. Finally, the economic component includes a spatially-explicit mathematical programing model which uses crop prices and production costs as inputs in addition to biomass transport costs and biophysical parameters from the first two models. The general structure of the bioeconomic model is summarized in Figure 1.

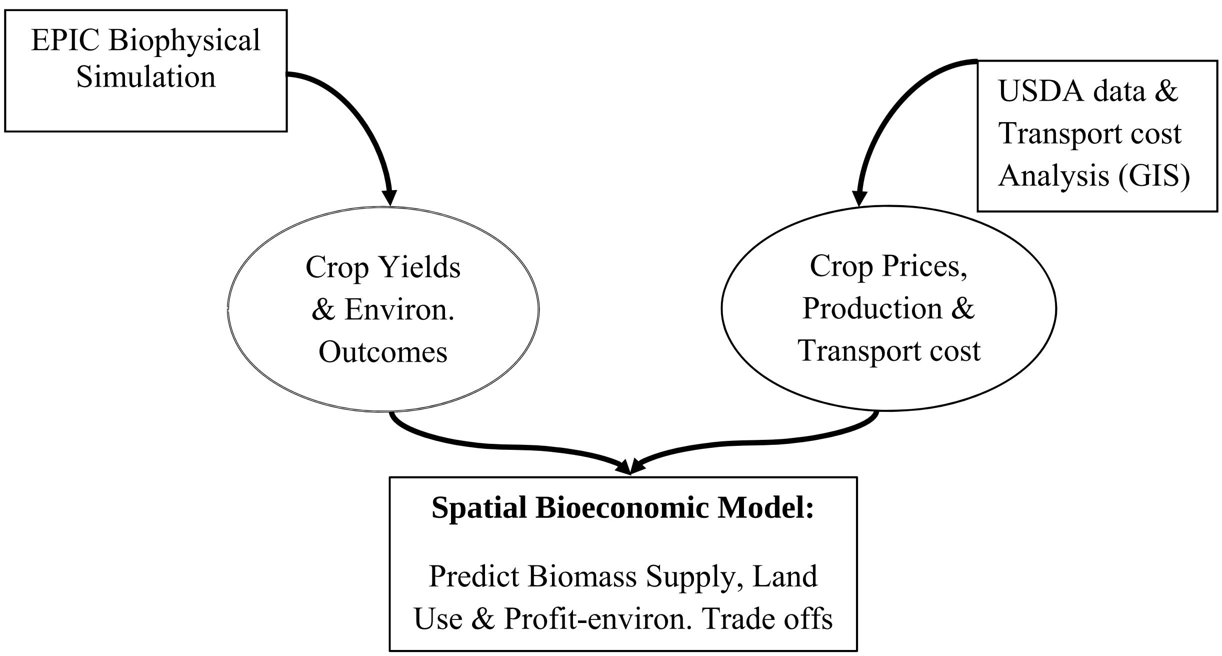

Figure 1: The structure of the bioeconomic model

2.2.1 Biophysical crop growth and environmental fate model (EPIC)

EPIC is a comprehensive terrestrial ecosystem model capable of simulating many biophysical processes such as plant growth and element cycling (water, carbon, and nitrogen) as influenced by climate, landscape, soil, and management conditions [18]. The spatially-explicit integrative modeling framework (SEIMF) developed by Zhang et al. [19] is employed to execute EPIC to provide biomass yield and relevant environmental variables. A minimum set of soil properties (e.g. albedo, soil layer depth, soil texture, soil bulk density, and soil carbon concentration) are needed to run EPIC. Salient processes modeled include growth and yield of numerous crops, herbaceous and woody vegetation; carbon dioxide (CO_2) and nitrous oxide (N_2O) fluxes; water and wind erosion; and the cycling of water, heat, carbon (C) phosphorus (P) and nitrogen (N).

2.2.1.1 Plant Growth and Biomass Yield

The plant growth sub-model of EPIC uses the concept of radiation-use efficiency by which a fraction of daily photosynthetically-active solar radiation is intercepted by the plant canopy and converted into plant biomass. Daily gains in plant biomass are affected by vapor pressure deficits, atmospheric CO_2 concentrations, environmental controls and stresses. Stress indices for water, temperature, N, P, and oxygen (O_2) availability are calculated daily to reduce potential plant growth and crop yield. Four processes are simulated to determine root distribution: a) the increasing depth of the rooting front, b) the length/weight ratio of new roots, c) the proliferation of roots within soil layers, and d) senescence [20]. Currently, EPIC is parameterized for about 120 plant species, including food crops, native grasses and trees. Up to ten plant species may compete for light, water and nutrients in a single land unit (plot, field, or small uniform watershed) [21]. In this work, we consider both food crops and lignocellulosic bioenergy feedstock; therefore, the biomass yield is defined by two yield components (grain/seed and cellulosic biomass). Biomass yield of all cropping systems scenarios are estimated using the environmental, edaphic, and past management conditions of the region, in order to estimate the production of various feedstock necessary to supply cellulosic biofuel and also provide the necessary information to analyze the potential competition between bioenergy and food production in a region.

2.2.1.2 Water and nutrients

The amount and quality of water from watersheds containing agricultural ecosystems is an important component of sustainability evaluation [22]. Water balance components calculated by EPIC include snowmelt, surface runoff, infiltration, soil water content, percolation, lateral flow, water table dynamics, and evapotranspiration [18]. EPIC simulates the N cycle in soil, including atmospheric N inputs, fertilizer and manure N applications, crop N uptake, denitrification, mineralization, immobilization, nitrification, ammonia volatilization, organic N transport on sediment, and nitrate-nitrogen (NO_3-N) losses in leaching, surface runoff, lateral subsurface flow, and tile flow [20]. Organic N loss to streams is estimated by a loading function developed by McElroy et al. [23] and modified by Williams and Hann [24]. Amounts of NO_3-N contained in runoff, lateral flow, and percolation are estimated as products of the volume of water and NO_3-N concentration in different flow components [18]. EPIC simulates the P cycle in soil by considering inputs through fertilizer and manure P applications, crop P uptake, mineralization, immobilization, organic P loss, and soluble P runoff. Sediment transport of P is simulated with a loading function as described in the organic N transport. The soluble P runoff equation is a linear function of soluble P loss in the top soil layer, runoff volume, and a linear adsorption isotherm [18].

2.2.1.3 Soil erosion

Soil erosion represents a major environmental threat to the sustainability and productive capacity of agricultural land [25]. In EPIC, the wind erosion continuous simulator (WECS) [26] is employed to compute wind erosion. This approach estimates potential wind erosion for a smooth bare soil by integrating the erosion equation through a day using the wind speed distribution. Potential erosion is adjusted using four factors based on soil properties, surface roughness, cover, and distance across the field in the wind direction. Several equations based on the Universal Soil Loss Equation are available to simulate water erosion [18]. The sediment yield is calculated as a function that integrates soil erodibility factor, crop management factor, erosion control practice factor, slope length and steepness factor, coarse fragment factor, runoff volume, and peak runoff rate [18].

2.2.1.4 Greenhouse gas (GHG) emissions

Proper accounting of the total GHG emissions generated from production of biofuels is an important factor in considering the overall sustainability of biofuel production [28]. In our modeling framework, we have modified the EPIC model to simulate GHG emissions (i.e. CO_2 and N_2O) associated with different crop production systems. The total GHG emissions is composed of three major components $GHGs\ emission = \Delta SOC + \Delta PlantC + C_{prod} + C_{N_2O}$ .Where $\Delta SOC + \Delta PlantC$ gives the gross C balance of the ecosystem and the gross C exchange between the land and the atmosphere. ΔSOC (kg C ha^{-1}) is the change in soil organic carbon stock between two periods; $\Delta PlantC$ (kg C ha^{-1}) is the change in plant biomass carbon between two periods; C_{prod} (kg C ha^{-1}) represents carbon-equivalent emissions associated with the production, distribution, and use of materials, both man-made (e.g. pesticides and fertilizers) and natural (e.g. seeds and water for irrigation) [29]. The C_{N_2O} is the calculated carbon equivalent emission (kg C ha^{-1}) of N_2O emission (kg N_2O-N ha^{-1}). We assumed the global warming potential (GWP) of N_2O is 298 times of that of CO_2 based on the latest assessment report from the Intergovernmental Panel on Climate Change [30]. The EPIC model was further enhanced with a new algorithm to estimate N_2O flux due to microbial denitrification under anaerobic condition [31]. Soil C dynamics is simulated in EPIC by a coupled carbon and nitrogen cycle [32]. For this work, the carbon balance in EPIC was revised and modified to account for both living and dead vegetation.

2.2.2 Mathematical programming model

Economic behavior is modeled from the standpoint of a representative farmer endowed with land resources in each sub-watershed at levels described by resource vector b, who chooses among a set of crop production systems and related market activities X so as to maximize his gross margin (revenues minus relevant costs). The problem of the representative farmer can be written as a linear constrained maximization program where the total net revenue is maximized subject to a set of land resource constraints [33]. The general problem can be mathematically expressed as

$$\operatorname*{Max}_{X} f(X) \tag{1}$$

Subject to

$$AX \leq b \tag{2}$$

$$DX = d \tag{3}$$

$X\ is\ k \times 1, A\ is\ m \times k, D\ is\ m \times k\ and\ b, d\ are\ of\ dimension\ m.\ A\ and\ D$ are matrices of crop and environmental yield coefficients, respectively. Constraint (2) is the set of land resource availability constraints and constraint (3) is a set of accounting rows that calculate the environmental outputs from chosen activities X, equal to d. Since the objective function (1) is linear, the solution to this problem leads to an unrealistic allocation of all the resources to the most profitable activity, a problem known as overspecialization. To avoid this problem, the model is calibrated using positive mathematical programming (PMP) techniques. The calibrated PMP model uses a quadratic objective function with decreasing marginal yield assumption that helps replicate closely the variety of observed activities in the region of study [34, 35].

The resulting calibrated PMP model is

$$\mathrm{Max}_X\, f(X) + \alpha'\mathrm{X} - \frac{1}{2}X'\Sigma\mathrm{X} \tag{4}$$

Subject to

$$AX \leq b \tag{5}$$

$$DX = d \tag{6}$$

where α is a $k \times 1$ marginal linear yield intercepts and Σ is a $k \times k$ positive definite matrix of the slopes of linear yields that capture declining marginal product with expanding land use. The values of α and Σ are calculated from the land resource shadow prices, prices of outputs sold and the observed activity levels from an intermediary model constrained by actual observed activity levels [34]. The resulting calibrated model (4)-(6) will be used to derive output supplies and land use response to various agricultural and land policies.

2.3 The Empirical Bioeconomic Model

The empirical bioeconomic model is built on the economic behavioral assumption that a representative farmer would select among a set of 74 cropping systems (see Table 1) to which he allocates land resources to maximize returns over stated costs. The modeling region is defined by nine counties divided into 37 subwatersheds, represented by 10-digit hydrological unit codes (HUC). The subwatersheds, in turn, are subdivided into good and poor quality cropland, represented by Land Capability Classes (LCC) 1-4 for good cropland and LCCs 5-7 for poor cropland. Since not all subwatershed has both good and poor cropland, there are a total of 71 land units.The cropping systems simulated are defined in terms of three management practices: crop rotation, fertilization and tillage. In all, we simulate the production of 13 crops managed via 74 potential cropping systems. So given expected crop yields, production and transport costs, the representative farmer allocates resources among various cropping systems to grow crops that maximize expected returns over 71 land units. The mathematical statement of the empirical model is expressed as follows:

$$\underset{x_{ij}}{\text{Max}} \sum_{i=1}^{71}\sum_{j=1}^{74}\left[-c_j x_{ij} - \sum_{m=1}^{3} r_m o_{mj} x_{ij} + \sum_{k=1}^{15} p_k a_{ijk} x_{ij} + \sum_{n=1}^{5} q_n e_{nj} x_{ij}\right] - \sum_{h=1}^{9} TC_h \tag{7}$$

Subject to

$$\sum_{j}^{74} x_{ij} \leq\ b_i\,, \forall\, i = 1\ to\ 71, \tag{8}$$

$$\sum_{i=1}^{71}\sum_{j=1}^{74} e_{nj} x_{ij} \leq \Gamma_n, \forall\, n = 1\ to\ 5, \tag{9}$$

$$\sum_{i}^{71}\sum_{j}^{74} a_{ijh}\, x_{ij} * (\beta + \gamma y_i + \theta z_i) = TC_h, \qquad \forall\, h = 1\ to\ 9, \tag{10}$$

$$\sum_{h}^{9}\sum_{i}^{71}\sum_{j}^{74} a_{ij}\, x_{ij} = \Psi. \tag{11}$$

h is a set 9 biomass outputs,

i is a set of 71 land units defined by subwatershed and land quality,

j is a set of 74 cropping systems simulated on each land unit,

k is a set of 15 grain or biomass crop products (13 crops with corn and wheat offering both grain and biomass outputs),

m is a set of 3 fertilizer nutrients (nitrate, phosphate and potash) used in the cropping systems,

n is a set of 5 environmental outputs produced from the cropping systems,

a_{ijk} is the yield of crop k from land parcel i and cropping system j,

b_i is the maximum quantity of cropland available in watershed i,

c_j is the average cost of production for cropping system i,

e_{nj} is the environmental yield n of system j ,

o_{mj} is the quantity per hectare of nutrient m used in cropping system j,

p_k is the market price of crop k,

q_n is the subsidy or the cost of the environmental output n ,

r_m is the unit cost of fertilizer nutrient m,

Γ_n is the quantity limit of environmental outputs allowed,

TC_h is the cost of transporting biomass product h to the demand point

Ψ is the total quantity of all biomass produced in the region,

x_{ij} is the quantity of land i allocated to cropping system j,

$(\beta + \gamma y_i + \theta z_i)$ is the transport cost of one metric ton (Mg) of biomass to the refinery site; with β being the cost of loading and unloading, γ is the cost per mile of hauling distance and θ the cost per hour of hauling time. The variables y_i and z_i are respectively the hauling distance and time from a parcel i to the refinery plant site.

The objective function (7) contains five expressions. The first expression $(-\sum_i^{71}\sum_j^{74} c_j x_{ij})$ represents the total variable production cost in all cropping system and watershed land units. The second expression $(-\sum_i^{71}\sum_j^{74}\sum_{m=1}^{3} r_m o_{mj} x_{ij})$ is the total cost of synthetic fertilizers across systems and land units. The third expression $(\sum_i^{71}\sum_j^{74}\sum_{k=1}^{15} p_k a_{ijk} x_{ij})$[4] is the total crop sales revenue from all cropping systems and watershed land units. The fourth expression $(\sum_i^{71}\sum_j^{74}\sum_{n=1}^{5} q_n e_{nj} x_{ij})$ is the sum of each environmental output across all cropping systems and land units. The last expression $(\sum_{h=1}^{9} TC_h)$ represents the total transport cost of biomass to

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[4] This expression is later modified to a quadratic form in the calibration process transforming the model into a nonlinear optimization program as mentioned in section 2.2.2. The quadratic form is obtained by writing $a_{ijk} = \rho_k - \phi_k x_{ij}$, where $\rho_k$and ϕ_k is the average yield intercept and slope for crop k . For details, refer to Howitt (1995).

the refinery plant. Equation (8) is the expression of the 71 land resource constraints. Equation (9) is a set of constraints enabling the creation of limits on permitted environmental output levels, while the last two accounting equations (10) and (11) are respectively used to calculate transport costs and total biomass quantity.

Table 1: Summary of simulated cropping systems

Rotation	**Tillage**	**Fertility**	**Residue removal & percent**	**Rotation length (years)**	**Number of cropping systems**
Alfalfa-Alfalfa-Alfalfa-corn-corn	Till or No-till	Medium or High	Yes (50%) or No (0%)	5	8
Continuous corn	Till or No-till	Medium or High	Yes (50%) or No (0%)	1	8
Corn-soybean-canola	Till or No-till	Medium or High	Yes (50%) or No(0%)	3	8
Corn-soybean	Till or No-till	Medium or High	Yes (50%) or No (0%)	2	8
Corn-soybean-wheat	Till or No-till	Medium or High	Yes (50%) or No (0%)	3	8
Grass mix of 5 types	No-till	Medium or High	-	24	2
Grass mix of 6 types	No-till	Medium or High	-	24	2
Miscanthus	No-till	Medium or High	-	24	2
Native prairie cool season	No-till	Medium or High	-	24	2
Native prairie warm season	No-till	Medium or High	-	24	2
Hybrid poplar	No-till	Medium or High	-	12	2
Switchgrass	No-till	Medium or High	-	24	2
Alfalfa-Alfalfa-Alfalfa-corn(for silage)-corn (for silage)	Till or No-till	Medium or High	-	5	4
Continous corn (for silage)	Till or No-till	Medium or High	-	1	4
Corn (for silage)-soybean-canola	Till or No-till	Medium or High	-	3	4
Corn (for silage)-soybean	Till or No-till	Medium or High	-	2	4
Corn (for silage)-soybean-wheat	Till or No-till	Medium or High	-	3	4
All systems					**74**

3. Parameterization of the model

The bioeconomic model is driven by four types of parameters. These are variable production costs, market prices, transport costs and simulated yields (of both crops and environmental outcomes).

3.1 Production cost parameters (c_j)

Production cost are calculated using custom machine work rates for all farming operations such as disking, planting, cultivating, fertilizer application, harvesting and baling. Production costs for field crops (corn, soybeans, soybeans, alfalfa, corn silage and canola) are calculated using crop budgets (for information on seed costs and fertilizer nutrients) and machine work rates (for information on farming operation costs) from Stein [36, 37]. The advantage of using such data is that it combines both variable labor and allocated fixed equipment costs for farming operations from planting to harvest. Similarly, we use the machine work rates [36] with additional information on seed and planting cost from previous research on cellulosic energy crop profitability analysis [9] to calculate production costs for all the cellulosic energy crops.

3.2 Crops market price (p_k) *fertilizer nutrients prices* (r_m) *and land resources parameters* (b_i)

Crop market price parameters used are primarily average prices for each of the 6 field crops (corn, soybeans, wheat, alfalfa, canola and corn-silage) over the period of 2007-09. All crop price data are collected from U.S. Department of Agriculture's (USDA) National Agricultural Statistics Service (NASS) data bases [38]. Note that biomass prices for cellulosic energy crops and crop residues are zero in the model as no market exists for such crops. Land use data for corn, soybeans, wheat, alfalfa and canola are obtained from USDA-NASS [38] but alfalfa area data are derived from the USDA cropland data layer (CDL). Prices of fertilizer nutrients, including nitrate, phosphate and potash, prices were obtained from Stein [37].

3.3 Transportation cost parameters ($\beta, \gamma, \theta, y_i, z_i$)

GIS is used to identify travel time (y_i) and distance (z_i) between biomass supply areas and biorefinery demand points in southwestern Michigan. Thirty-seven 10-digit watersheds are modeled across nine counties of southwest Michigan (Allegan, Barry, Eaton, Van Buren, Kalamazoo, Calhoun, Cass, St. Joseph and Branch). Transport costs are measured from the centroids of these 37 sub-watersheds to a one central potential biorefinery site located at the city of Kalamazoo (see Figure 2). The network dataset is set up in two connectivity groups to accommodate limited highway access. The state of Michigan digital framework roads version 9a is used to create the network. Roads are classified based on the Michigan department of transportation (MDOT) national function class (NFC). The three major types of roads in this classification system are arterial, collector, and local. Within these three classes, the roads are subdivided into thirteen urban and rural categories. The road network does not have speed limits associated with the features and speed limits are assigned by MDOT NFC class and were derived from comparison of multiple factors. Actual speed limit is derived from representative roads in Michigan. These are compared to speeds used in standard commercial applications such as Google maps, MapQuest, and Yahoo Maps. Actual speed limits are then reduced by 15%-60% for non-interstates and are reduced by 5% for interstates to closely relate to the speeds used in commercial applications. The other inhibitor to take into consideration is that the Michigan road network does not account for stop lights, stop sign, or traffic. These reduced speeds will hopefully account for those factors and serve a more realistic image of transportation costs. The value of parameters regarding the loading and unloading costs , the per kilometer hauling distance cost and the per hour hauling time cost θ are graciously obtained and updated from Graham, English and Noon [12] paper.

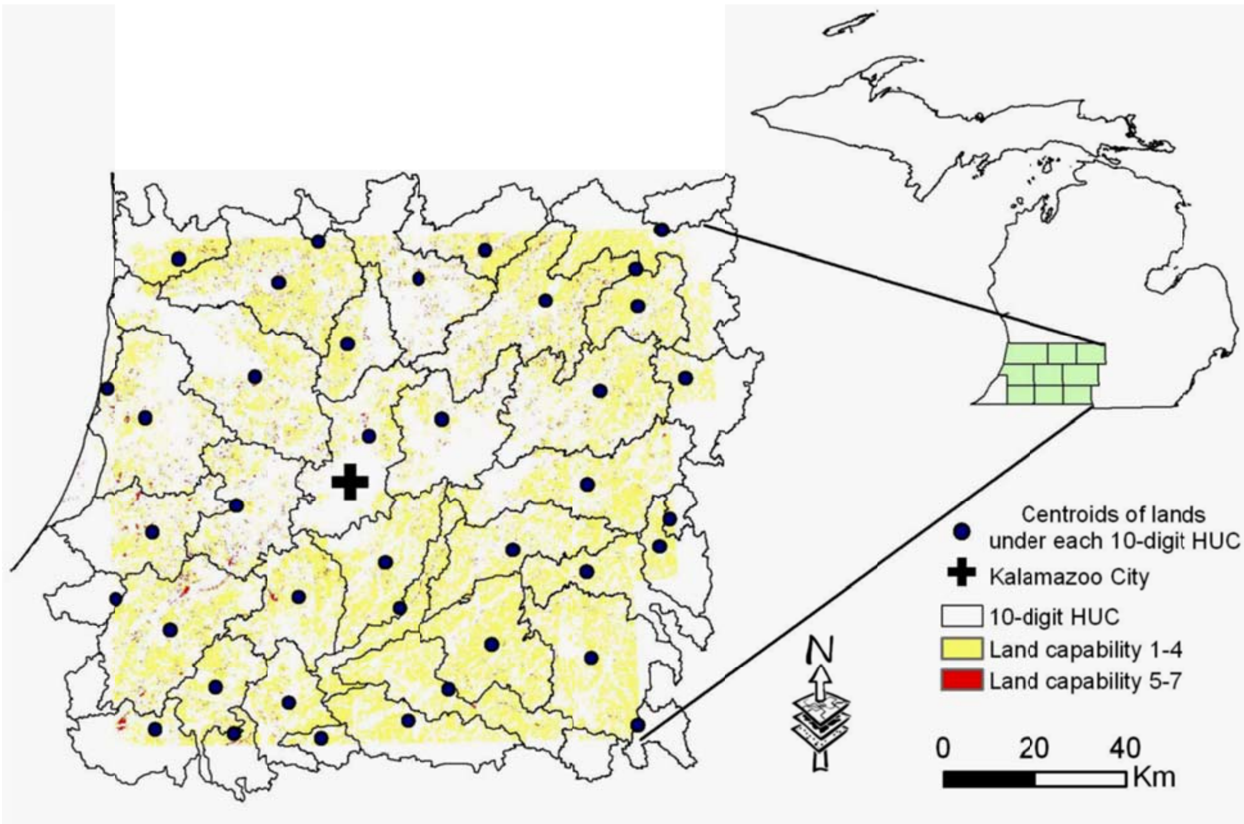

Figure 2: Map of the southwest Michigan study area's nine counties subwatersheds (based on 10-digit hydrologic unit codes (HUC)).

3.4 Biophysical simulated yield parameters

The yield parameters used are mean values from site specific EPIC simulations over the period of 1986 to 2009 of 6 traditional field crop grain and silage yields, 7 cellulosic crop biomass yields and 2 field crop biomass residue yields. Field crop yields include corn, soybean, wheat, alfalfa, canola and corn-silage yield. Cellulosic energy crop biomass yields include switchgrass, poplar, miscanthus giganteus, native prairie cool season mix, native prairie warm season mix, grass mixes of 5 types (switchgrass, big bluestem, little bluestem, altai wildrye, indian grass) and grass mixes of 6 types (which includes lespedeza in addition to the first 5 types). Crop residues include corn stover and wheat straw yields. The values of all these parameters and the data sources are given in table 2.

Table 2: Parameters used in the empirical bioeconomic model for southwest Michigan

Parameters	Values	Units	Source
Field crop prices			
Corn	163.60	$/Mg	2007-2009 average from USDA-NASS
Soybean	364.87	$/Mg	
Wheat	241.07	$/Mg	
Alfalfa	147.11	$/Mg	
Canola	400.95	$/Mg	
Silage	49.82	$/Mg	Estimated by Authors
Fertilizer nutrient prices			
Nitrate(N)	0.95	$/Kg	2007-2009 average from Stein (2010)
Phosphate (K)	0.94	$/Kg	
Potash(P)	1.00	$/Kg	
Land use validation parameters			
Corn	252,230	ha	2007-2009 average from USDA-NASS
Soybean	172,895	ha	
Wheat	26,142	ha	
Alfalfa	26,828	ha	
Canola	0	ha	
Silage corn	9,186	ha	
Transport cost parameters			
Loading and unloading	3.37	$/Mg	Updated from Graham et al. (2000)
Hauling distance cost	0.09	$/Mg-km	
Hauling time cost	4.26	$/Mg-h	
Simulated EPIC mean yields			
Corn	6.14	Mg/ha	1986-2009 average simulated from EPIC
Soybeans	1.96	Mg/ha	
Wheat	2.98	Mg/ha	
Alfalfa	5.82	Mg/ha	
Canola	1.96	Mg/ha	
Corn Silage	12.18	Mg/ha	
Switchgrass	14.29	Mg/ha	
Poplar	4.65	Mg/ha	
Miscanthus	19.53	Mg/ha	
Native prairie - cool season	8.38	Mg/ha	
Native prairie - warm season	7.82	Mg/ha	
Grass mixes of 5 types	12.15	Mg/ha	
Grass mixes of 6 types	12.75	Mg/ha	

4. Validation and Calibration of the Empirical Models

4.1 EPIC output validation

The algorithms in EPIC have been tested on numerous occasions using site specific data [39]. In this study, EPIC was used to make regional predictions of biomass yields and environmental variables for which few databases are available for comparison. For corn and wheat grain yields, soybean seed yields, and corn silage yields, we compared the yearly results simulated by EPIC for 1986-2009 aggregated at county scale against yearly county-scale data reported by the USDA- NASS. For new biofuel crops not reported by USDA-NASS and other environmental variables, we compared our simulation results with observations from the Long-term Ecological Research experiment in place since 1988 at the Kellogg Biological Station of Michigan State University.

4.2 Bioeconomic Model Calibration

The bioeconomic model is calibrated using 2007-09 average prices and land use to mitigate problems that often arise from calibration to a potentially anomalous single year. The model calibration follows the usual three steps described in previous PMP research works [34, 35]. In the first step a raw linear model was run and we found that only alfalfa, corn and soybeans were grown in two different cropping systems across all the 71 pieces of land. To bring the model to a realistic representation of the variety of crops that are grown in the region, we ran a second model in which land use was constrained by the observed land data from USDA-NASS. The final calibrated model is a nonlinear model that runs under the assumption of decreasing linear marginal yields. The goal of this assumption is to account for nonlinearity that arises from declining yield at the extensive margin, first formalized by David Ricardo but often omitted in quantitative models [40].The coefficients of each of the linear marginal yield functions are calculated using information on shadow prices calculated in the preceding model. The calibrated model has a percentage absolute deviation (PAD) of 14.5%. Previous literature on agricultural sector models have been considered valid for forecasting purposes if their PAD values do not exceed 15% [33, 35].

5. Empirical Results

5.1 Evolution of biomass supply in response to price

Considering that bioenergy crops are scarcely grown in southern Michigan at this time, our initial research question was: Under what price conditions would biomass production becomes attractive to profit-oriented farmers? To answer this, the bioeconomic model was solved sequentially using biomass prices from $1/Mg to $200/Mg. The corresponding biomass supply and sources, environmental outputs and land use change were recorded and graphed in Figure 3. We found that the first biomass sources offered are byproducts of grain production, corn stover at a biomass price of $21/Mg, followed by wheat straw at $27/Mg. These biomass sources need only cover the added costs of harvest and transport, because they are byproducts of crops already produced for their grain. However, the total amount of biomass available from crop residues (corn stover and wheat straw) is quite limited in the region, only 6 x 10^5 Mg. Crop residues begin to be supplemented by switchgrass when the biomass supply price reaches $46/Mg, and they are completely replaced by switchgrass at $61/Mg. Switchgrass is the sole source of biomass supply for prices from $61 to $118/Mg, creating a regional biomass supply plateau at 7.0 x 10^6 Mg. When the biomass price reaches $118/Mg switchgrass is supplemented by biomass from small amounts of mixed grasses (only 80 Mg total from mixed grasses), making little difference to the overall biomass quantity up to a price of $154/Mg. Finally, at this price, miscanthus giganteus[5], the highest yielding biomass crop, becomes profitable. As biomass prices rise even higher, miscanthus compensates its exceptionally high establishment cost and gradually displaces switchgrass and mixed grasses.

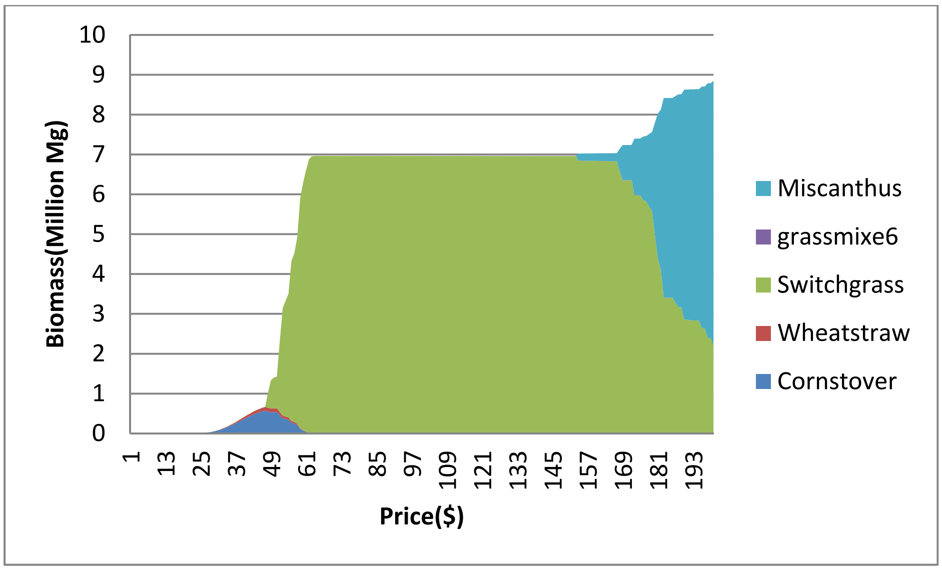

Figure 3: Predicted sources of regional cellulosic biomass supply as function of biomass price ($/Mg), nine county area of southwest Michigan.

Our biomass supply response predictions fall in the range of recent published estimates. Differences are attributable to yield variability in various geographical regions of study and the fact that our model accounted for opportunity cost that these previous research have not included. Recent studies have found the delivered cost of switchgrass to range from $30 to $43/Mg, including $37/Mg in the southern plains of the United States [13], a mean of $39/Mg in Tennessee, and between $30/Mg and $43/ Mg in the Midwest region [41]. Previous studies on

[5] Note that although miscanthus has the highest yield among all the cellulosic energy crops grown in the study. It has also the highest establishment cost that makes it less competitive in the current setting. Future rhizomes cost decreases may make it more profitable as studies in James et al. [9].

miscanthus range from a high biomass price to breakeven with corn net revenue of about $200/Mg for southwest Michigan [9] to a delivered cost of $44-80/Mg in Illinois [42]. There are only a few studies on biomass supply from crop residues. A study of biomass supply from crop residues including corn, wheat, sorghum , barley, oats and rice residues [43] found that the delivered supply price lies between $15/Mg and $42/Mg depending on the region (Corn Belt, Great Plains, Delta or Southeast). The supply prices are lower in the most fertile regions such as the Corn Belt. Our estimated prices for corn stover and wheat straw are within this range of prices. Another study on corn stover supply and availability estimated the delivered cost at $48/Mg without storage and preprocessing costs [44].

5.2 Land use and grain crop level change as function of biomass price

Our second research question asked: What is the sequence of crop production systems and associated land uses as biomass supply is increased? Land use change, crop grain production and biomass supply are all linked. This link can be explained following the various changes observed in the biomass supply, as illustrated in Figure 4. As farmers start supplying crop residues for biomass (at $21/Mg for corn stover and $27/Mg for wheat straw), wheat production and associated land use increase. The reason for the increase is that the wheat production systems (a corn-soybean-wheat rotation) supplies crop residues from both corn and wheat and therefore becomes more profitable for farmers. The switchgrass production at $46/Mg causes a sharp increase in switchgrass land use and a decrease in the crop grain production and land use. When biomass prices reach $61/Mg, switchgrass has displaced all crop grain production, so all land use becomes dedicated to switchgrass. At biomass prices above $61/Mg, land use can only switch to other sources of biomass.

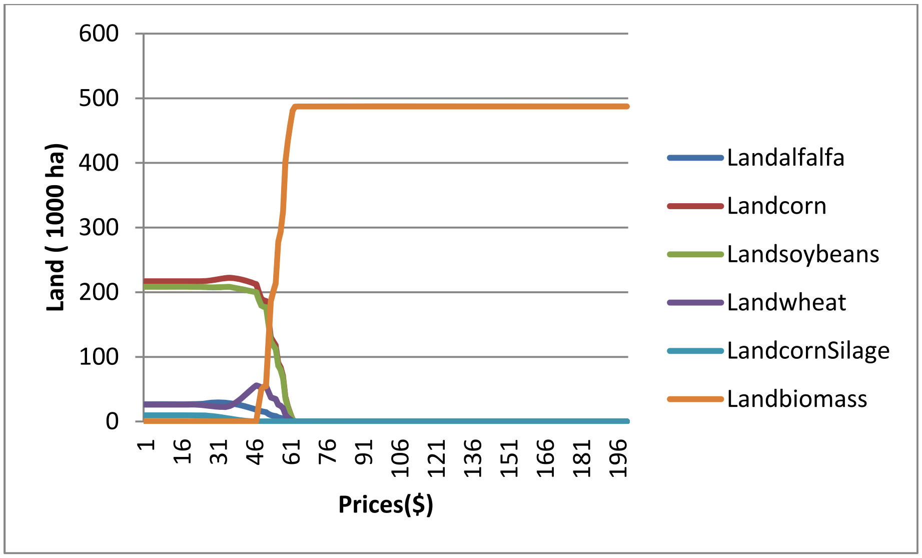

Figure 4: Predicted land use change for crops in response to changing biomass price ($/Mg), nine county area of southwest Michigan.

5.3 Environmental impact of biomass production activities

Our third research question was: What are the environmental consequences of the changing crop production systems as biomass production increases? To understand the impact of biomass supply activities on the environment, we illustrate trade-offs between profitability and environmental outputs in a series of charts in Figure 5. We found that the changes in all environmental outputs follow a similar trend. Crop residue removal increases losses of soil, NO_3, and soil C, while reducing P losses and emissions of N_2O. When perennial cellulosic energy crops begin to displace annual crops, we see a gradual improvement in environmental outputs. Since all these cellulosic energy crops are perennial and need no tillage after planting and only modest levels of nitrogen fertilizer, an increase of their production leads to reduced greenhouse gas emissions (CO_2 and N_2O) and improved water quality by reducing soil erosion as well as NO_3 and P losses.

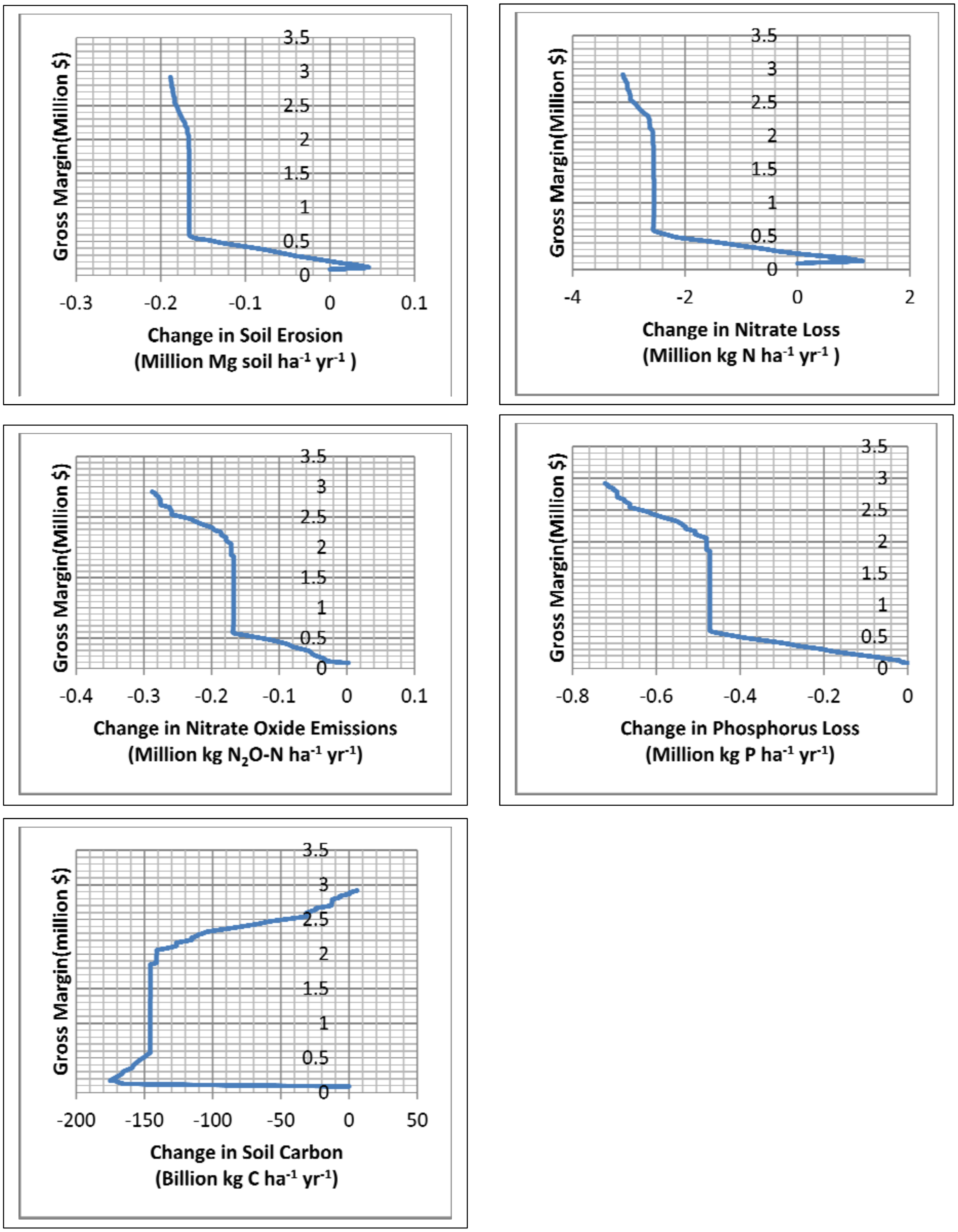

Figure 5: Profitability-environmental quality trade-offs as cellulosic biomass production rises, nine county area of southwest Michigan.

Our results on the environmental impacts are comparable to previous research. State level environmental impact study of producing switchgrass in Tennessee found that replacing conventional field crops by switchgrass may result in less soil erosion and soil nutrient loss [12].

5.4-Impact of biomass crop assistance program (BCAP) on biomass supply

The final research question was: How are these results altered by the provisions of the Biomass Crop Assistance Program (BCAP), a feature of the Food, Conservation and Energy Act of 2008. Biomass crop establishment costs represent a large proportion of their production costs, and the BCAP policy offers growers a cost share of 75 % of seed and planting costs. To evaluate the impact of this policy on biomass supply, we simulated a scenario of biomass production under BCAP by granting 75% subsidy for seed and planting costs on all energy crops production. (We did not explicitly simulate the BCAP sale price cost share, because this is implicitly covered by the model's sequential changes in biomass price). As illustrated in Figure 6, we found that supply schedules for corn stover and wheat straw are unchanged. However, perennial grass crop supply is sensitive to the BCAP establishment cost share provision. Predicted switchgrass supply starts at $45/Mg instead of $46/Mg. More important, miscanthus giganteus, which has the largest establishment cost due to expensive rhizomes, comes into production with BCAP at $63/Mg instead of $154/Mg. Grass mixes are not produced under this policy scenario because of their lower yields relatively to switchgrass and miscanthus. The maximum quantity of biomass produced under BCAP is higher and reached at lower supply price (9.5 million Mg reached at $89/Mg), whereas the maximum biomass supply modeled without BCAP was 8.8 million Mg reached at $200/Mg. Clearly, the BCAP policy has the potential to impact the supply, acceptable price and lowest cost source of biomass. There is no major change in the trend of land use change under BCAP, only the threshold points where changes occur. Consequently, the environmental outputs follow the same trend as before except that they start improving at lower profit level when switchgrass and miscanthus production begin.

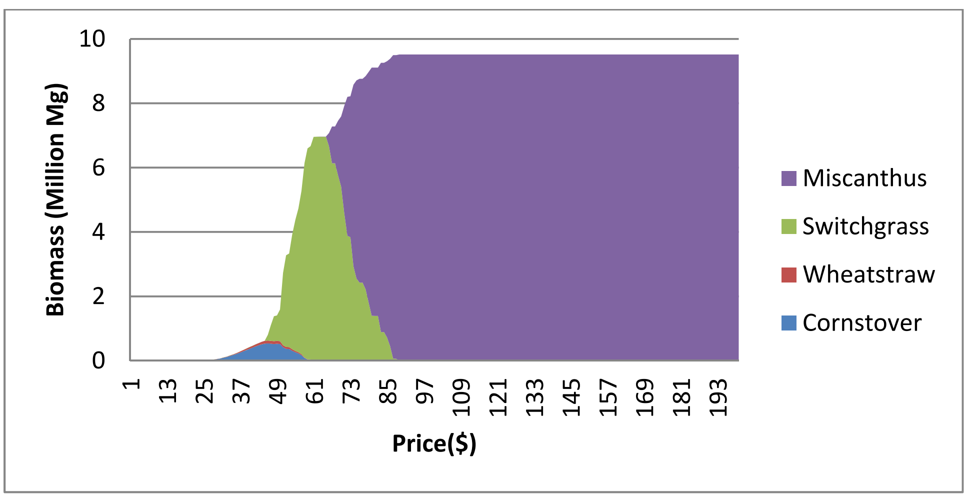

Figure 6: Predicted sources of regional cellulosic biomass supply under the USDA Biomass Conversion Assistance Program (BCAP) as function of biomass price ($/Mg), 9 county area of southwest Michigan.

6. Conclusion

This paper describes a new, spatial bioeconomic model to study the potential regional supply of cellulosic biomass by representative, rational, profit maximizing farmers. Having been calibrated to fit with observed farmer behavior, the calibrated model captures the typical farmer decision making process and enables study of likely responses to unfamiliar market prices and public policies. The model can predict changes in crop production, cropland use and environmental quality at the regional landscape level with greater detail and depth than existing national models. While currently designed for mean values of key parameters, the model can be adapted to accommodate dynamics and risk through recursive programming and adjustment of yield and price parameters.

An empirical application of the model to southwest Michigan predicts that as biomass price rises, farmers are likely to supply biomass initially in the form of crop residues (corn stover and wheat straw). Corn stover production starts at \$21/Mg and wheat straw production starts at \$27/Mg (delivered price at the biorefinery or similar demand point). However, biomass supplies from crop residues are predicted to increase greenhouse gas emissions (CO_2 and N_2O) and deteriorate water quality with increased nutrient loss (P and N losses). Biomass supplied from perennial, dedicated energy crops will become attractive starting at higher prices (\$46/Mg for switchgrass, \$118/Mg for grass mixes and \$154/Mg for miscanthus giganteus) but with better environmental outcomes. Greenhouse gas emission levels and soil nutrient losses are predicted to improve with perennial energy crop production. The paper also evaluates the impact of the farm bill's Biomass Crop Assistance Program on biomass supply and predicts that the 75 % subsidy on energy crop establishment costs will lower the minimum biomass supply prices for switchgrass to \$45/Mg (from \$46/Mg) and for miscanthus to \$63/Mg (from \$154/Mg). The BCAP impact is significant for miscanthus, which currently has much higher establishment costs than the other bioenergy crops. Land use and environmental outputs trend are found to not change under BCAP.

This bioeconomic model represents the integration of spatially and temporally detailed biophysical simulation with economic decision making. The model's integrated assessment builds on knowledge from plant and soil sciences, geography and economics. The bioeconomic model provides a valuable tool for exploring a number of important research questions related to biomass production and environmental consequences at the regional level. Examples of such questions include, a) How could environmental policy incentives be designed to encourage more sustainable biomass cropping practices? b) How would the siting of a biorefinery or biomass fueled power plant affect the spatial patter of crop biodiversity? and c) How would future bioenergy, agricultural or agro-environmental policies affect profitable crop production and environmental consequences at the regional level? Such questions will be the focus of future analyses based on this model.

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